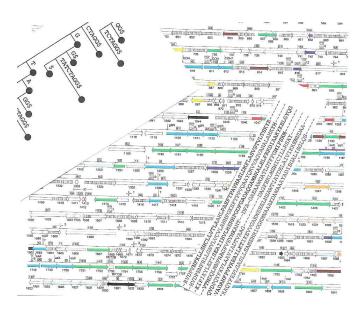
Lecture 4: Data Base searchers with BLAST and FASTA, scoring statistics

Introduction to Computational Biology

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Why database searches

- Gene finding
- Assigning likely function to a gene.
- Identifying regulatory elements
- Understanding genome evolution.
- Assisting in sequence assembly
- Finding relations between genes

Search engines:

3 main components:

- Scoring function
- Algorithm
- Statistical model to recover significant results

Important issue: speed

Local alignment

- Local alignment seeks similar segments of unspecified length from the 2 sequences being compared.
- Rigorous method is local dynamic programming (last class), time is proportional to the product of lengths of sequences it compares.
- BLAST is linear time *heuristic* algorithm.

BLAST

- Basic Local Alignment Search Tool a family of most popular sequence search program including: Basic BLAST, Gapped BLAST, Psi BLAST
- Main idea (basic BLAST): Homologous sequences are likely to contain a short high scoring similarity region a hit. Each hit gives a seed that BLAST tries to extend on both sides

Some BLAST terminology

word – substring of a sequence word pair – pair of words of the same length. score of a word pair – score of the gapless alignment of the two words:

VALMR

V A K N S Score=-4+3+-4+-3+-1=-9 (PAM120)

HSP – high scoring sequence pair.

Main steps of BLAST

- Parameters: w = length of a hit; T = min. score of a hit (for proteins: w=3, T=13 (BLOSUM62)
- Step 1: Given query sequence Q, compile the list of possible words which form with words in Q high scoring word pairs.
- Step 2: Scan database for exact matching with the list of words complied in step 1.
- Step 3: Extending hits from step 2.
- Step 4: Evaluating significance of extended hits from step 3.

Step 1: Find high scoring words

- For every word x of length w in Q make a list of words that when aligned to x score at least T.
- Example: Let x=AIV then score for AIA is 5+5+0 (dropped) and for AII 5+5+4 (taken)
- Number of words in the list depends on w and T, and is much less than 20³ (typically about 50)

Step 1

MVRERKCILCHIVYGSKKEMDEHMRSMLHHRELENLKGRDIS

GSE

```
Query word, W=3 for proteins 1
(W=11 for nucleotides)
                      Word Score (BL-62)
                      GSK 15
                      GAK 12
                      GNK 12
                      GTK 12
                      GSR 12
                      GDK 11
                      GQK 11
                      GEK 11
                      GGK 11
                      GKK 11
                      GSQ
```

Step 2 – Finding hits

- Scan database for exact matching with the list of words compiled in step1:
- This can be done efficiently using techniques as hash table (requires preprocessing of a data base)

Step 2

MVRERKCILCHIVYGSKKEMDEHMRSMLHHRELENLKGRDIS

```
      Query word, W=3
      ↓

      Word Score (BL-62)

      GSK 15 GAK 12 GNK 12 GSR 12

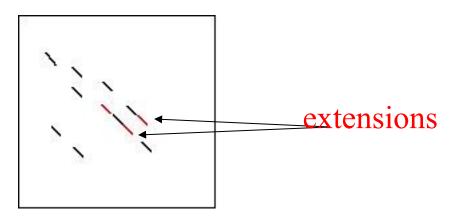
      GDK 11 GQK

      11 GGK 11 GKK 11 GSQ 11 GSE 11 Threshold for hits, T=11
```

```
Query 1 MVRERKCILCHIVYGSKKEMDEHMRSMLHHRELENLKGRD 40
MVRERKCILCHI++GS+KEMDEHMRSMLHHRELENLKGR+
Sbjct 1 MVRERKCILCHIIHGSEKEMDEHMRSMLHHRELENLKGRE 40
```

Step 3: Extending hits

- Parameter: X (controlled by a user)
- Extend the hits in both ways along diagonal (ungapped alignment) until score drops more than X relative to the best score yet attained.
- Return the score highest scoring segment pair (HSP).



Statistical Significance of BLAST scores

Is the score high enough to provide evidence of homology?

Are the scores of alignments of random sequences higher than this score?

What are is the expected number of alignments between random sequences with score greater than this score?

BLAST statistics- intuition

- Given a 0/1 sequence of length k
- Probability of all ones: 1/2^k
- Sequence of k consecutive one in a sequence length k+1?
- $1-(1-1/2^k)^2$
- Sequence of length k+n?
- $1 (1-1/2^k)^{n+1}$

Two probes

• The longer the sequence, the more likely you are going to get k ones by chance!

More intuition

- The probability will depend on:
 - How long is are the sequences (the longer the easier to get local score above treshold by chance)
 - Scoring matrix
 - Distribution of amino acids in each sequence

Score statistics

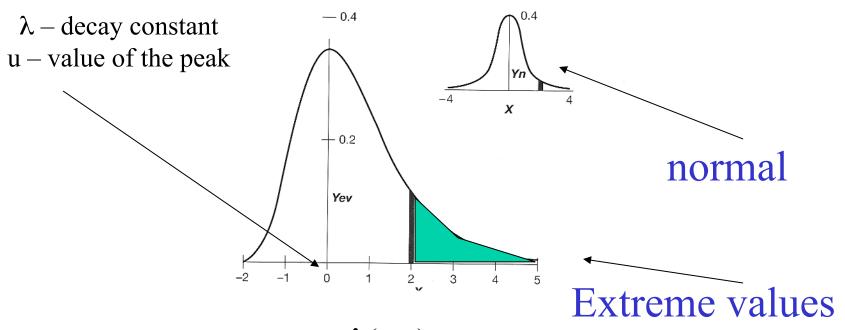
- If one knows the null distribution of the scores (scores of alignment of unrelated sequences) then we can assess the significance
- In order to solve this problem we will focus first on local alignments that do not contain any gaps.
- Karlin and Altschul (PNAS,1990) provided a theory for ungapped high-scoring segments HSPs.

Karlin and Altschul provided a theory for computing such probability

• Assumptions:

- the scoring matrix M must be such that the score for a random alignment is negative;
- n, m (lengths of the aligned sequences) are large
- The amino acid distribution p(x) is in the query sequence and the data base is the same
- Positive score is possible (i.e. M has at least one positive entry).

Score of high scoring sequence pairs follows extreme value distribution



$$P(S < x) = \exp(-e^{-\lambda(x-\mu)})$$
 thus:
 $P(S > = x) = 1 - \exp(-e^{-\lambda(x-\mu)})$

Extreme value distribution for sequence alignment

Property of extreme value distribution:

$$P(S < x) = \exp(-e^{-\lambda(x-\mu)}) \rightarrow$$

$$P(S>=x) = 1 - \exp(-e^{-\lambda(x-\mu)})$$

 μ – location (zero in the fig from last slide), λ scale;

For random sequence alignment:

$$\mu = \ln \text{Kmn}/\lambda$$

K- constant that depends on p(x) and scoring matrix M Since 1-exp(-x) ~ x and substituting for μ and σ :

$$P(S>=x) \sim e^{-\lambda(x-\mu)} = Kmn e^{-\lambda x}$$

E=value-expected number of random scores above x

• E-value = $KNme^{-\lambda x}$

(Expected number of sequences scoring at least x observed by change, it is approximately same as p value for p value < 0.1)

Normalization

After normalization to by setting

$$S' = (\lambda S - \ln K)/\ln 2$$

we get "bit score" S' such that

$$E = Nm 2^{-S'}$$
 (blast e-value)

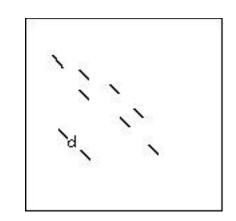
Bit scores from various scoring matrices can be compared directly

For BLAST tutorial visit

http://www.ncbi.nlm.nih.gov/BLAST/

Refinement of the basic algorithm-the two hit method

- Observation: HSP of interest are long and can contain multiple hits relatively short distance away.
- Central idea: Look for non-overlapping pairs of hits that are of distance at most d on the same diagonal.

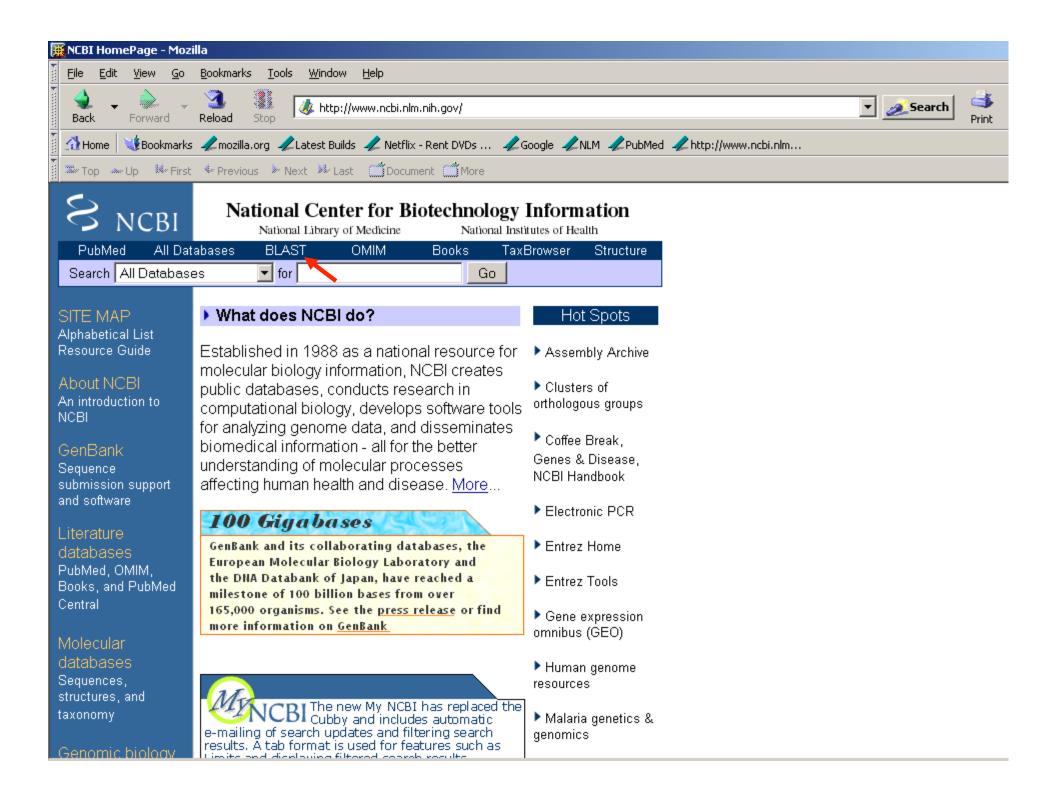


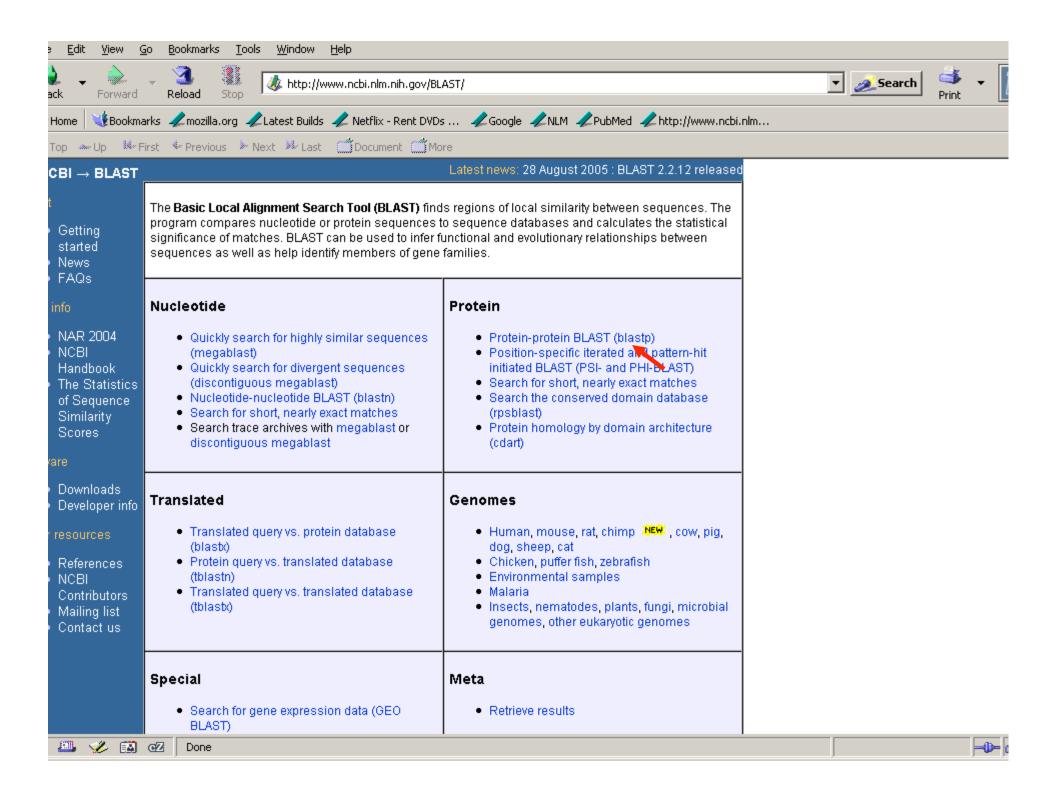
• Benefits:

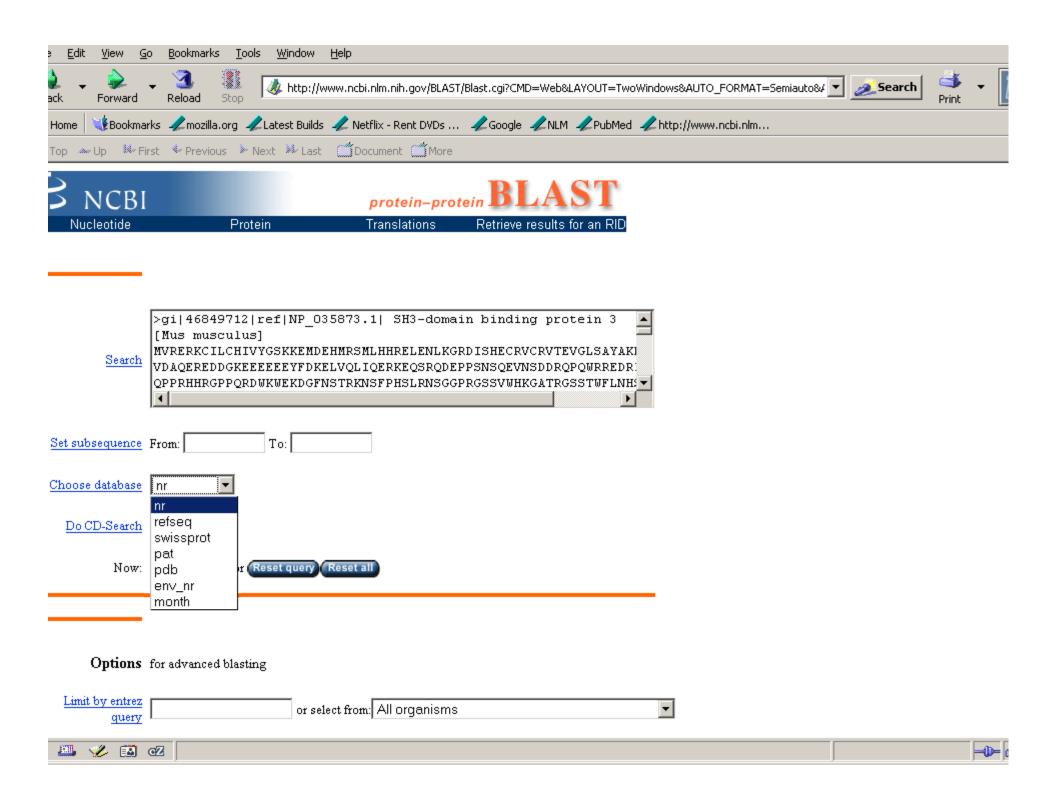
- can reduce word size w from 3 to 2
 without loosing sensitivity (actually sensitivity of two-hit BLAST is higher).
- Since extending a hit requires a diagonal partner, smaller number of hits are being extended results in increased speed.

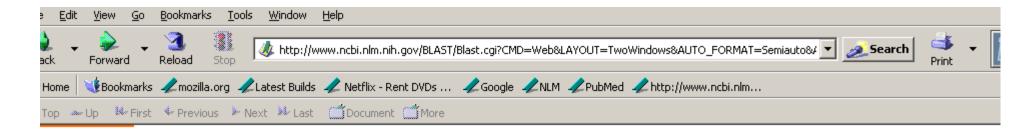
Gapped BLAST statistics

- Theory for ungapped BLAST does not extend easily
- Simulations indicate that for the best hits scores for local alignment follow extreme value distribution
- Method approximate λ and μ to match experimental distribution λ and μ can be computed form median and variation of the experimental distribution.
- BLAST approach simulate the distribution for set of scoring matrices and a number of gap penalties. BLAST offers choice of parameters form this precomputed set..

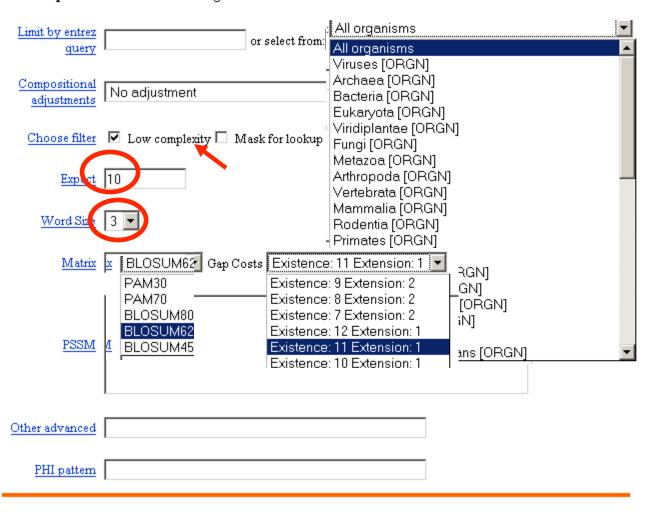








Options for advanced blasting

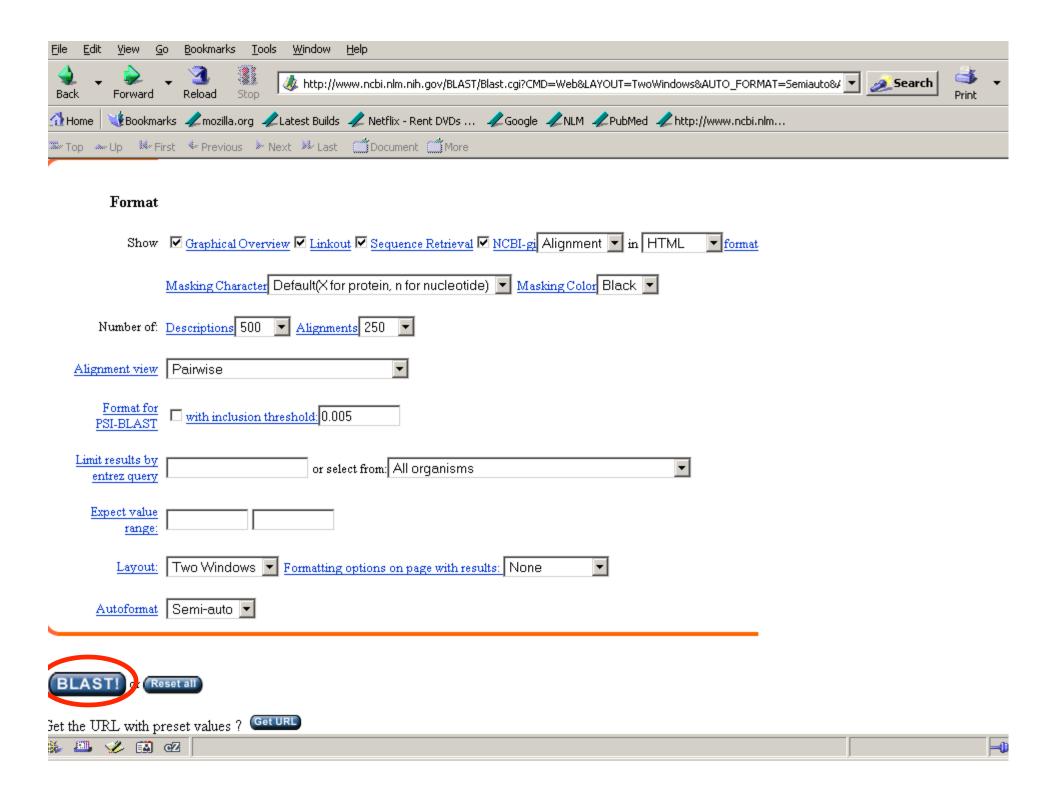


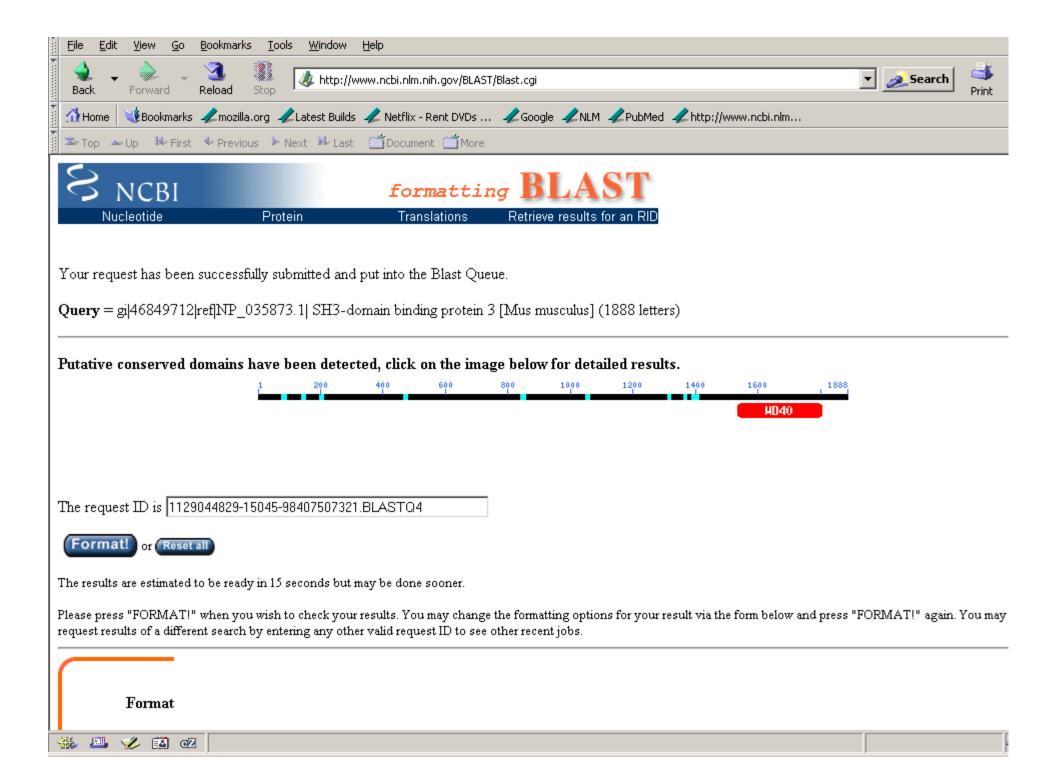


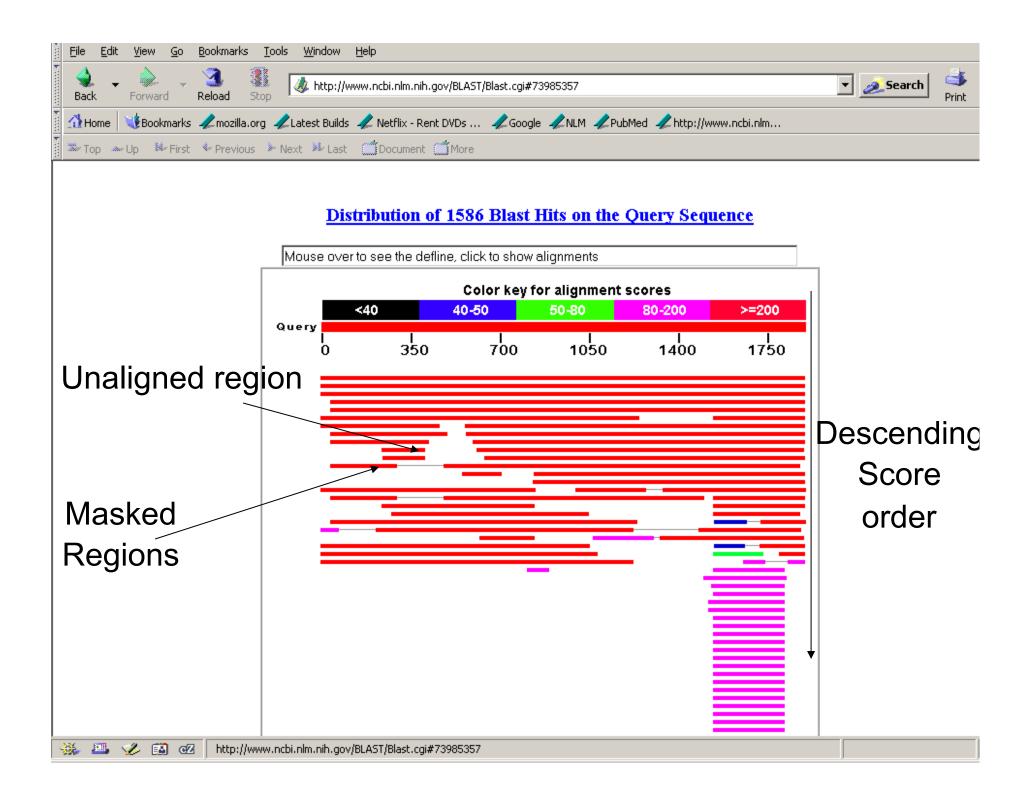


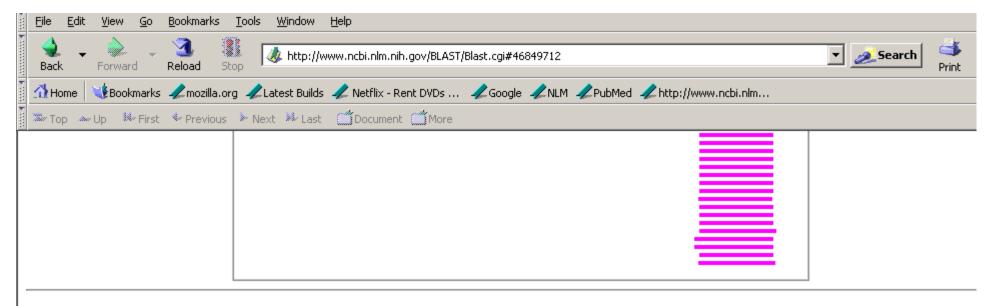
Low complexity regions

- In some protein sequences there are regions with low information content (the "low complexity regions) e.g. regions that contains that have a large number of, say, leucine; or repeats
- But, since BLAST assumes uniformly-distributed amino-acid sequences
- BLAST provides possibility to mask such regions: (BLAST has the filter turn ON by default.)





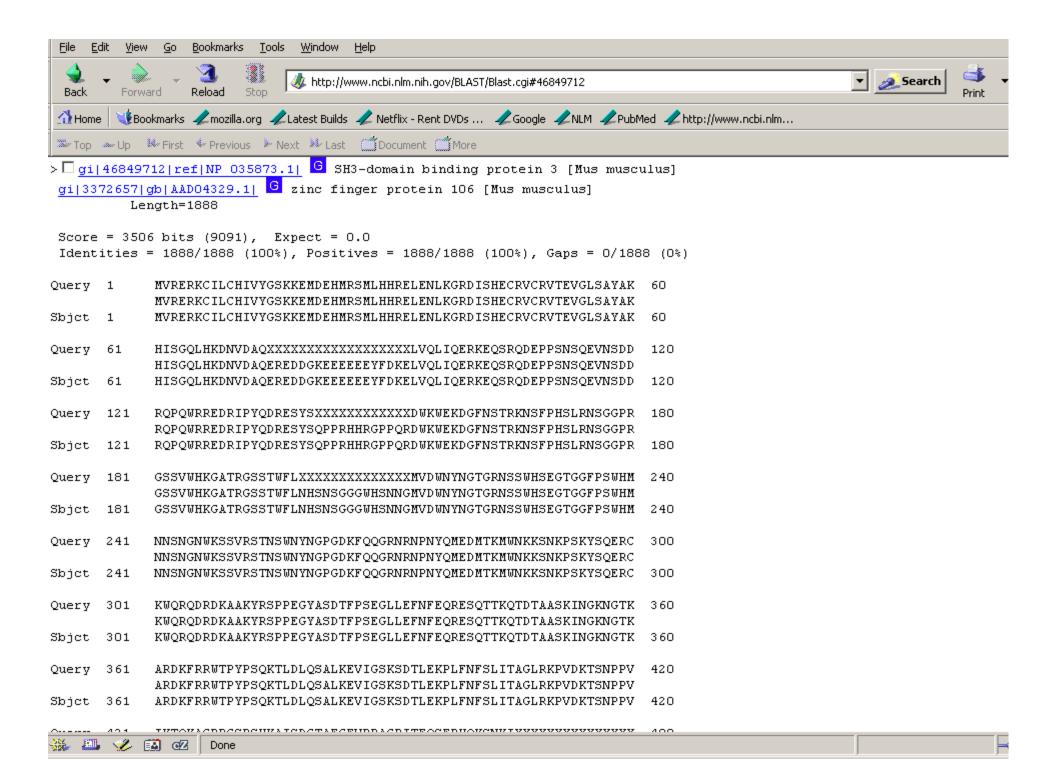




Related Structures

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Sequences producing significant alignments:	Score (Bits)	E Value	
gi 46849712 ref NP 035873.1 SH3-domain binding protein 3 [Mu	3506	0.0	G
gi 51702166 sp 088466 ZF106 MOUSE Zinc finger protein 106 (Zf	3464	0.0	G
gi 73999869 ref XP 535441.2 PREDICTED: similar to zinc finge	2583	0.0	G
i 11968023 ref NP 071918.1 zinc finger protein 106 homolog	2561	0.0	G
i 73999867 ref XP 849689.1 PREDICTED: similar to zinc finge	2506	0.0	G
i 19343547 gb AAH25424.1 Zfp106 protein [Mus musculus]	2253	0.0	G
i 30722445 emb CAD91142.1 hypothetical protein [Homo sapiens]	1923	0.0	G
i 30722348 emb CAD91149.1 hypothetical protein [Homo sapiens]	1920	0.0	G
i 30268259 emb CAD89926.1 hypothetical protein [Homo sapiens]	1895	0.0	G
i 55642057 ref XP 523059.1 PREDICTED: hypothetical protein XP_	1883	0.0	G
i 30722295 emb CAD91147.1 hypothetical protein [Homo sapiens]	1868	0.0	G
predicted: similar to zinc finge	1757	0.0	G
ri 30722288 emb CAD91134.1 hypothetical protein [Homo sapiens]	1583	0.0	G
i 73999865 ref XP 859468.1 PREDICTED: similar to zinc finge	1555	0.0	G
i 74196164 dbj BAE32992.1 unnamed protein product [Mus musc	1551	0.0	G
gi 61815391 ref XP 603433.1 PREDICTED: similar to zinc finge	1184	0.0	G



Some rules of thumb

• Significant hits for protein searches:

E-value < 1e-03

Percent of identity $\geq 25\%$

Significant hits for nucleotide searches:

E-value ≤10⁻⁰⁶

Percent of identity $\geq 70\%$

Variants BLAST Algorithms:

Program	Query	Database
BLASTN	Nucleotide	Nucleotide
BLASTP	Protein	Protein
BLASTX	Nucleotide, six- frame translation	Protein
TBLASTN	Protein	Nucleotide, six- frame translation
TBLASTX	Nucleotide, six- frame translation	Nucleotide, six- frame translation

Position Specific Iterated BLAST

- Collect all database sequence segments that have been aligned with query sequence with E-value below set threshold (default 0.01)
- 1. Construct position specific scoring matrix for collected sequences. Rough idea:
 - Align all sequences to the query sequence as the template.
 - Assign weights to the sequences
 - Construct position specific scoring matrix
- 2. Find sequences that mach the profile
- Iterate (1) and (2)

Sequence to run an example

LSADQISTVQASFDKVKGDPVGILYAVFKA31DPSIMAKFTQFAGKDLESIKGTA PFETHAN61RIVGFFSKIIGELPNIEADVNTFVASHKPR91GVTHDQLNNFRA GFVSYMKAHTDFAGAEAA121WGATLDTFFGMIFSKM

FASTA

Heuristic algorithm, similar to BLAST.

Main idea (expanded on next slides):

- Step 1 : Find hot-spots (hot spot ~ hit in BLAST)
- Step 2: Locate best "diagonal runs" (sequences of consecutive hot spots on a diagonal)
- Step 3 : Combine sub-alignments form diagonal runs into a longer alignment
- Step 4: Find alternative local alignments.

Step 1 FASTA

• A Lookop table is used to find identities (ktup=1) or runs of identities

Lookup table for sequence 1:

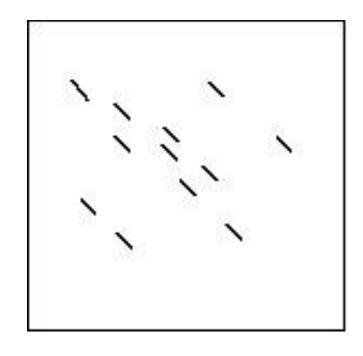
Step 2 of FASTA

Locate best diagonal runs (gapless alignments) Give positive score for each hot spot

- Give negative score for each space between hot spots
- Find best scoring runs
- Score the alignments from the runs and find ones above a threshold. These are possible "sub-alignments"

Step 3 of FASTA

- Combine sub-alignments into one alignment.
- We need to solve a problem known as the chaining problem: find a collection of non-contradicting subalignments that maximize some scoring function.
- Problem reduces to a problem close to maximum common subsequence.



Step 4 of FASTA

Find alternative local alignments

• Use dynamic programming restricted to a ribbon along the diagonal containing best run found in step 3.

Statistical significance estimation (in the absence rigorous theoretical model)

- Collect alignment scores of this sequence to other random sequence (exclude extremes)
- Compute average score, (ave.) and standard deviation, (sdiv).
- Compute z-score:
 - Z = (score-ave score)/sdiv
- Estimate P(Z>z) (under the assumption of extreme value distribution)

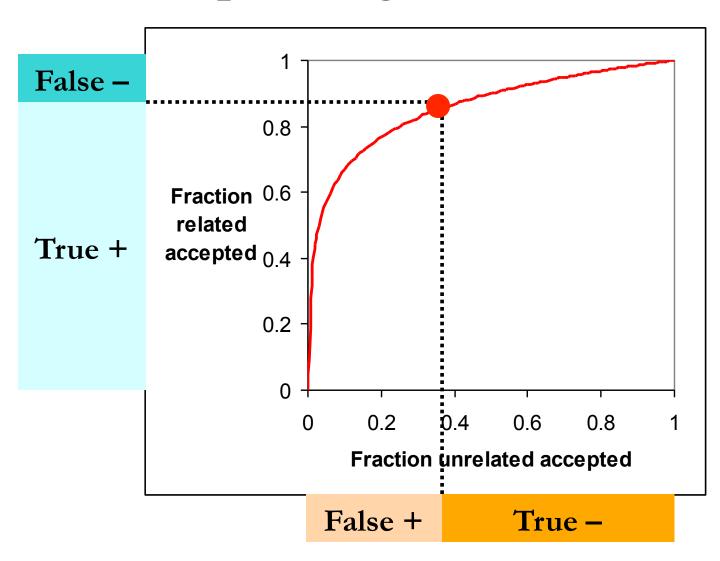
Comparing methods' retrieval accuracy

- Let's assume we have a new method to perform a search and we would like to compare with BLAST and FASTA, or just BLAST Vs. FASTA.
- First, we need to create a gold standard (of correct answers) for benchmarking (for example proteins known to be homologous based on structure comparison.)
- Idea: For each estimate how many answer it get wrong.
- Problem: The answer depends in the score threshold: for example setting high score threshold we are unlikely to recover any non-homolog but we are likely to miss a lot of homolog's
- Thus we have two types of errors: false positives and false negatives and both have to be taken into account in a comparison.

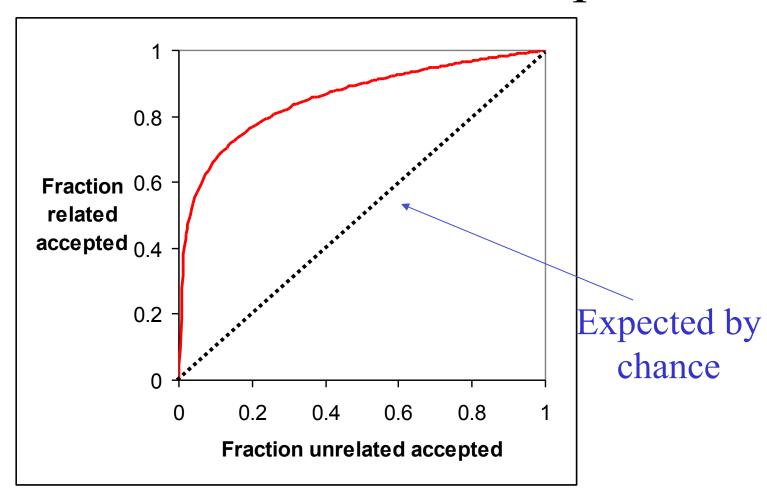
Sensitivity /Specificity of a data base search

	Related	Unrelated	Predictive
			value
Retrieved by the search	TP True Positive	FP False Positive	Positive (PPV) TP/(TP+FP)
Not retrieved by the search	FN False Negative	TN True Negative	Negative (NPX) TVN /(TVV+FXV)
	Sensitivity TP/(TP+FN)	Specificity TN/(FP+TN)	

Receiver Operating Characteristic curve



Random retrieval on a *ROC* plot



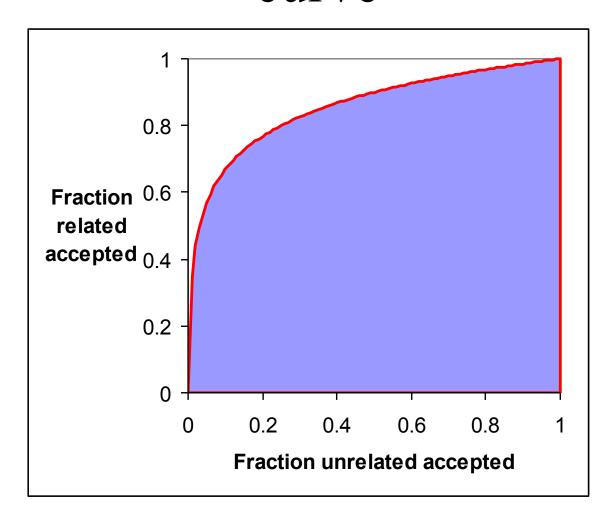
ROC curve

- Axis correlate with statistical measures:
- Sensitivity of the search=TP/(TP+FN)
- Specificity of the search=TN/(FP+TN)
- So ROC plots are plots of
- Sensitivity Vs. (1-Specificity)

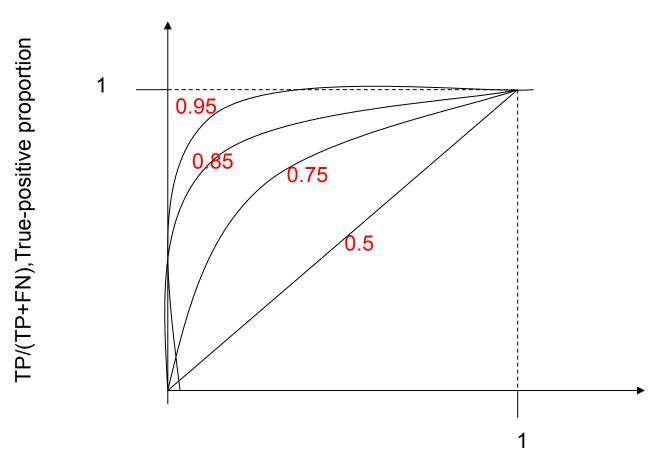
Comment:

Other measurements are used to do other variants of this plot

ROC score: area under the ROC curve



ROC scores – examples better method – higher ROC score



FP/(FP+TN), False-positive proportion

ROC_n

If the data base is huge but the set of true positives is small you one is often interested in how many true positives are recovered before you get a certain number of false positives.

That is you are not necessarily interested in what is the order of true and false positives after a certain number of errors (n)

ROC_n

Let i = 1,2,3 ... index the rank of the false positives, and let t_i be the number of true positives ranked ahead of the *i*th false positive.

ROC for *n* false positives, defined as:

$$ROC_n = \frac{1}{nT} \sum_{1 \le i \le n} t_i$$

T is total number of true positives in the database,